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Robust and resilient renovation solutions in different climate change scenarios

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Abstract. Building renovation is currently urgent in order to decrease the energy consumption of a building stock. In order to achieve robust renovation scenarios, uncertainty quantification is needed. Climate change scenarios are important factors and need to be included in the analysis. In this paper, three climate change scenarios are applied probabilistically for a renovation scenario using dimensionality reduction techniques and further uncertainty propagation. The results show that RCP2.6 provides more robust results and saves on average 2.10^5 CHF and 2.10^5kgCO2eq. in a building life cycle comparing to RCP 8.5. The analysis under climate change is also compared to the probabilistic calculations under current climate and the results show the underestimation of both costs and environmental impacts when climate change is not included. It can also be clearly seen that even under the best case of RCP 2.6, building renovation is urgently needed to decrease the environmental impacts and costs.

1. Introduction

The building sector is one of the largest sources of energy consumption and greenhouse gas emissions in the world [1]. The largest part of the energy demand in existing buildings occurs during the operational stage and, therefore, renovation of the building stock is crucial. However, the identification of both environmental and cost-effective solutions is difficult due to the large heterogeneity of the building stock and the associated uncertainties of some key parameters in a life cycle perspective. Such parameters include the reference service life of the materials, occupancy behavior, existing state of the building, electricity mix scenarios and climate change. The latter is one of the most important sources of uncertainty that have to be included in the analysis.

Different projections for climate change scenarios have been recently discussed and global warming has become one of the most important topics for scientific research. Based on the projections, Europe will experience in the future further warming and anthropogenic influence on the climate systems is clear. [2]. Three representative concentration pathways (RCP) as RCP2.6, 4.5 and 8.5, were estimated by the National Center for Climate Services (NCCS) in Switzerland. The ranges in the climate projections are scenario-based and therefore, are subject to uncertainties. The aim of the paper is to use the data provided by NCCS and include the climate change analysis probabilistically in the integrated analysis of Life cycle cost (LCC) and Life cycle assessment (LCA) for the building retrofit. By integrating climate change in the uncertainty quantification, we would like to see the influence of each RCP scenario on the LCC and LCA.

2. Methodology

In this paper, we propose a method to account for uncertainties during the life cycle of a building. We apply three climate change scenarios probabilistically for a renovation scenario of a residential building located in Switzerland in order to compare the climate change scenarios with the analysis under standard conditions. To do so, we analyze the data for the three climate change scenarios as proposed by the Swiss National Center for Climate Services in a probabilistic context. The detailed procedure is explained below.

2.1. Model description

The idea of the model is to create an integrated workflow for LCC and LCA calculations. First, the heating demand calculation is performed, following the procedure of the Swiss standard SIA 380/1 [3] with quasi-steady monthly results. The analysis includes the transmission and ventilation losses, as well as solar and internal gains. The cooling demand was also taken into account through the calculation of cooling degree days [4]. The heating and cooling demand is followed by LCC and LCA analyses. The stages of production, operation, replacement and demolition are included as system boundaries for both analyses. For LCC, the procedure of Swiss Center for buildings' rationalization (CRB) is followed [5].

Global warming potential (GWP) is considered as an indicator for the climate change based on the characterization factors from IPCC[6]. The metrics of analyses are kg.CO2eq. and CHF over the building's life cycle. The whole process is modelled using python programming language. The reference study period for the assessment is 60 years as defined by SIA 2032 [7].

2.2. Description of the climate data

In general, the climate in Switzerland is divided into four regions describing different climate zones defined by the National Center for Climate Services (NCCS)[2] (See Figure 1).

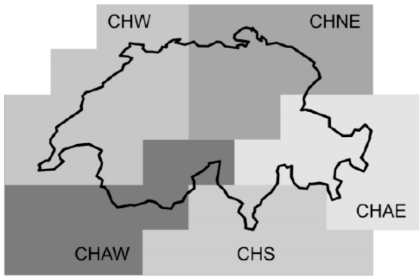

Figure 1. Climate zones in Switzerland[2].

The gathered data from the NCCS represent three different scenarios of anthropogenic forces over the 21st century which are generated using ten different projection models [2] [7]. These projections are built from a selection of regional climate models (RCM) from the most recent EURO-CORDEX ensemble [9]. RCMs are based on Global climate model (GLM) projections, refined accordingly with

Swiss complex topography using dynamical downscaling to increase the resolution of the simulations. The data is afterwards divided into five regions shown in Figure 1 and averaged into monthly temperature values. We then consider the CHW region which gathers data from 85 stations in a time period ranging from 1981 to 2099. The current study is solely focused on the change in the mean dry-bulb temperature, therefore, the change in precipitation, wind direction and solar irradiation are not taken into account. For solar irradiation, static monthly values are used for the assessment.

2.3. Uncertainty quantification

After the model is created and the outdoor dry-bulb temperature data are processed, further calculations are performed using the uncertainty quantification framework called UQLab [10]. Uncertainty quantification aims at identifying and quantifying all sources of uncertainties in a system with the aim of assessing how they influence the system response. Many studies were performed to assess the uncertainties in LCA and LCC [11]–[14]. Some consider climate change uncertainties [13] [14]. In general, such analysis is time-consuming as it requires a large number of evaluations of a computational model describing the system of interest. In this study, we use a metamodeling technique called *polynomial chaos expansion* (PCE) [17] in order to replace the computationally expensive model by an inexpensive surrogate. The metamodel is built on a set of polynomials of different degrees depending on the dimension of the model. The accuracy of the created metamodel is usually estimated using a leave-one-out error following a cross validation procedure. Practical details about building a PCE surrogate model can be found in Sudret (2007) [18].

To account for random temperatures in LCA/LCC calculations, the straightforward approach is to consider the 720 monthly temperatures (which corresponds to 60 years, the time span of the analysis) as independent random variables. This is however problematic as the dimension of the model that is to be approximated by PCE becomes extremely large. To make the problem more tractable, we resort to a dimensionality reduction technique, namely *principal component analysis (PCA) [20]*.

2.4. Temperature time-series generation

The idea of the approach is to generate random temperature time-series by learning the underlying distribution from the Swiss climate data described in the previous section. This is achieved by first reducing the data and then learning the underlying distribution of the resulting PCA coefficients in order to sample new ones[19], [20].

2.4.1. Dimensionality reduction using PCA

Let us also consider the temperature time-series as a K-dimensional random vector $\boldsymbol{T} = \{T_1, \ldots, T_K\}$ where each T_i, $i = \{1, \ldots, K\}$ represents a monthly temperature. Its covariance matrix is defined by

$$\boldsymbol{\Sigma} = \mathbb{E}[(\boldsymbol{T} - \mathbb{E}[\boldsymbol{T}])^T (\boldsymbol{T} - \mathbb{E}[\boldsymbol{T}])].$$

Principal component analysis proceeds by first considering the eigenvalue decomposition of the covariance matrix [21]:

$$\boldsymbol{\Sigma} = \mathbf{V\Lambda V}^T,$$

where $\mathbf{V}$ is a K×K matrix with the i_{th} column being an eigenvector denoted by $\boldsymbol{v}_i$ and $\boldsymbol{\Lambda}$ is a diagonal matrix such that diag $(\boldsymbol{\Lambda}) = \{\lambda_1, \ldots, \lambda_K\}$ with λ_i being the i_{th} eigenvalue.
The principal component decomposition of the random vector $\boldsymbol{T}$ then reads:

$$\boldsymbol{T} = \mathbb{E}[\boldsymbol{T}] + \textstyle\sum_{i=1}^{K} Z_i \boldsymbol{v}_i,$$

where Z_i is a random variable defined by:

$$Z_i = v_i^T (\boldsymbol{T} - \mathbb{E}[\boldsymbol{T}]).$$

The idea of PCA is that generally, a small portion of the eigenvectors is sufficient to represent the variability in the random vector $\boldsymbol{T}$. Hence an approximation of $\boldsymbol{T}$ can be obtained by retaining only $K' < < K$ terms with the corresponding largest eigenvalues:

$$\widetilde{\boldsymbol{T}} = \mathbb{E}[\boldsymbol{T}] + \sum_{i=1}^{K'} Z_i\, v_i$$

In practice, K' is chosen such that ε_{cut}% of the variability in $\boldsymbol{T}$ is explained in $\widetilde{\boldsymbol{T}}$, i.e. K' is the smallest integer such that $\sum_{i=1}^{K'} \lambda_{(i)} / \sum_{i=1}^{K} \lambda_{(i)} \geq \varepsilon\%$, where λ is defined such that $\lambda_{(1)} > \lambda_{(2)} > \cdots > \lambda_{(K)}$. In this work, we split the data into three sets of 20 years thus allowing us to have K = 240 < N = 260. Setting the threshold ε_{cut} to 95% leads to K' = 8 for each of the three subsamples. Therefore, the final dimensionality reduction is achieved by going from 720 to 24 random variables to describe the temperature time-series.

2.4.2. *Time-series sampling*

Let us now consider that we have N realizations $\boldsymbol{\mathcal{T}} = \{\boldsymbol{t}^{(1)}, \ldots, \boldsymbol{t}^{(N)}\}$ of the random vector $\boldsymbol{T}$. By empirically computing the covariance matrix $\widehat{\boldsymbol{\Sigma}}$ and proceeding to the developments above, we can obtain N realizations of $\boldsymbol{Z} = \{Z_1, \ldots, Z_{K'}\}$. The proposed idea is then to empirically learn the underlying joint distribution $\hat{f}_{\boldsymbol{Z}}$ of the random vectors $\mathbf{Z}$. In this work, we simply consider kernel density estimation, a non-parametric approach. Next, we can generate new samples $\hat{Z}_i \sim \hat{f}_Z$ and therefore derive new time-series as follows:

$$\widehat{\boldsymbol{T}} = \mu_{\boldsymbol{T}} + \sum_{i=1}^{K'} \hat{Z}_i\, \widehat{\boldsymbol{v}}_i\ ,$$

where $\mu_{\boldsymbol{T}}$ is the empirical mean of $\boldsymbol{\mathcal{T}}$ and $\widehat{\boldsymbol{v}}_i$ are the eigenvectors associated to the eigen-decomposition of $\boldsymbol{\Sigma}$.

3. Case study and a renovation scenario

To apply the developed methodology, a multi-family apartment building located in Western Switzerland is used as a case study and presented in Figure 2 The year of construction is 1972. The total energy reference area is 1440 m^2.

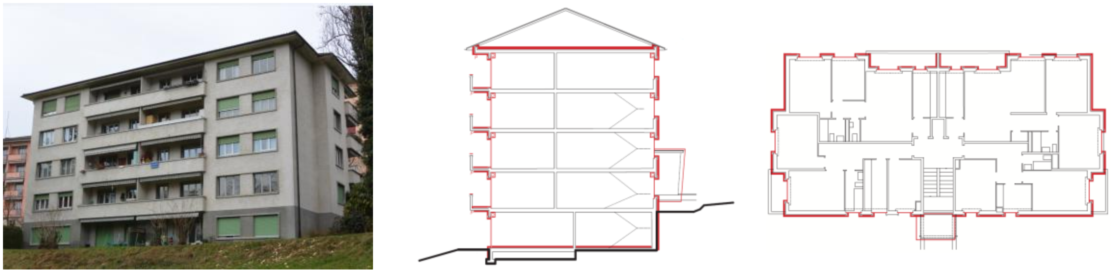

Figure 2 – Building representation, plan and section

In order to apply a renovation solution, the Swiss construction database called *Bauteilkatalog*, which follows e-BKP-H SN 506 511 structure, where each element contains several components [22], is used. To select a renovation solution, a method for identifying renovation solutions using the sensitivity analysis is adapted as shown in Galimshina *et al.*[23]. This leads to the renovation scenario presented in Table 1. Basic construction details can be seen in Table 1.

Table 1.Construction details of the selected building before and after renovation

Element	Before renovation	After renovation
Exterior walls	4cm mineral wool, U = 0.56 W/(m²K)	12 cm rockwool insulation and plaster, U – 0.25 W/m²K
Ground floor (shop)	2cm cork insulation in the shop, U = 1.4 W/(m²K)	10 cm rockwool insulation and solid wood, U – 0.25 W/m²K
Ceiling against attic	6cm mineral wool, U = 0.5 W/(m²K)	Not renovated
Windows	Double glazing with low-E layer, PVC frame, U_{frame} = 2 W/(m²K), $U_{glazing}$ = 1.1 W/(m²K), g_{value} = 0.55	Wooden-aluminum window 3 WS, frame part 10%, U – 0.8 W/m²K
Heating system	Oil boiler, low efficiency	Heat pump, air-to-water, COP 2.8

To account for all the sources of uncertainties, 44 parameters besides the climate change are included in this study. These parameters include the existing state of the building, materials production costs and impacts, building operation, occupancy behaviour and reference service life. The complete list of the parameters including their range and distribution can be seen in Table 2.

Table 2. Probabilistic description of the uncertain parameters used in the case study. The parameters column represents the upper and lower bounds of the uniform distributions while the moments show the mean and standard deviation when other distributions are concerned.

Parameters	Parameters	Moments	Distribution	Source
		Embodied GWP and investment costs		
Exterior wall GWP [$kgCO_2eq./m^2$]	[7, 13]		uniform	Mean values - [24], Uncertainty costs - [25], Uncertainty GWP – assumption [%] – [-30, 30]
Exterior wall cost [CHF/m^2]	[58.4, 84.1]		uniform	
Ground floor GWP [$kgCO_2eq./m^2$]	[4.02, 6.9]		uniform	
Ground floor cost [CHF/m^2]	[37.1, 55.7]		uniform	
Windows GWP [$kgCO_2eq./m^2$]	[53.1, 98.6]		uniform	
Windows cost [CHF/m^2]	[492.8, 739.2]		uniform	
Embodied GWP heating system (heat distribution+heat diffusion) [kgCO2-eq./ERA]	[0.685, 0.729]		uniform	[26]
Cost oil boiler [CHF/ERA]	[34.2, 51.3]		uniform	[25], [27]
Cost heat pump [CHF/ERA]	[40.7, 61]		uniform	
		Operational environmental and cost inputs		
Oil [kgCO2-eq./kWh]	[0.319, 0.322]		uniform	[26], [27]
Heat pump [kgCO2-eq./kWh]	[0.036, 0.039]		uniform	
Oil [CHF/kWh]		[0.093, 0.111, 0.128]	triangular	[26], [28]
Heat pump [CHF/kWh]		[0.064, 0.079, 0.093]	triangular	
Inflation rate [%]	[0.5,2]		uniform	[29]
Discount rate (real) [%]	[2.5,4.5]		uniform	[25]
		Components reference service life		
Exterior wall [years]		[40.6, 11.6]	lognormal	[30]
Slab [years]		[33.7, 14.2]	lognormal	
Wall against unheated surface [years]		[40.6, 11.6]	lognormal	
Windows [years]		[27.5, 12.2]	lognormal	
Oil boiler [years]		[19.4, 3.1]	lognormal	
Heat pump [years]		[17.1, 6.4]	lognormal	
		System performance		
Existing windows U-value [W/m^2*K]		[2.9, 0.58]	lognormal	Assumption
Existing exterior wall degradation		[10, 3]	gumbel	Assumption
Existing roof insulation degradation [%]		[20, 5]	lognormal	Assumption
Thermal bridge new building [%]		[18.15, 5]	gaussian	Assumption
Efficiency loss of the existing system [%]	[0.15, 0.25]		uniform	Assumption
Efficiency loss of a new system [%]		[0.15, 0.05]	gaussian	Dependent on the heating system
Existing slab against unheated surf., degradation [%]		[10, 5]	lognormal	Assumption
		User-oriented parameters		
Operating temperature inside [°C]	[20,23]		uniform	[31]
Building occupation schedule [h/day]	[8, 16]		uniform	+/- 4 hours to the suggested 12 h value by [46]
Airflow existing building [m^3h/m^2]	[0.7, 1]		uniform	[31]

4. Results

The input uncertainties are propagated through the PCE model using crude Monte Carlo simulation. In the following figures, the resulting distributions of both LCA and LCC are shown. They are obtained through kernel smoothing of the model responses histograms. The comparison of three climate change scenarios alongside with the results of the renovation scenario under uncertainties but without climate change is shown in Figure 3. As it was expected, with RCP 2.6, lower LCA results are achieved (mean value – **277 500** $kgCO_2eq$.) while with RCP 8.5, the mean value is **498 900** $kgCO_2eq$. It is worth mentioning that the standard deviation for RCP 2.6 is also considerably smaller (**36 000** $kgCO_2eq$), while the standard deviation for RCP 8.5 is **76 500** $kgCO_2eq$. There is also a considerably big overlapping area between RCP2.6 and 4.5. It can also be clearly seen that the climate change and is crucial to be included in the analysis as the results of the same applied renovation scenario without climate change is underestimating CO_2 emissions.

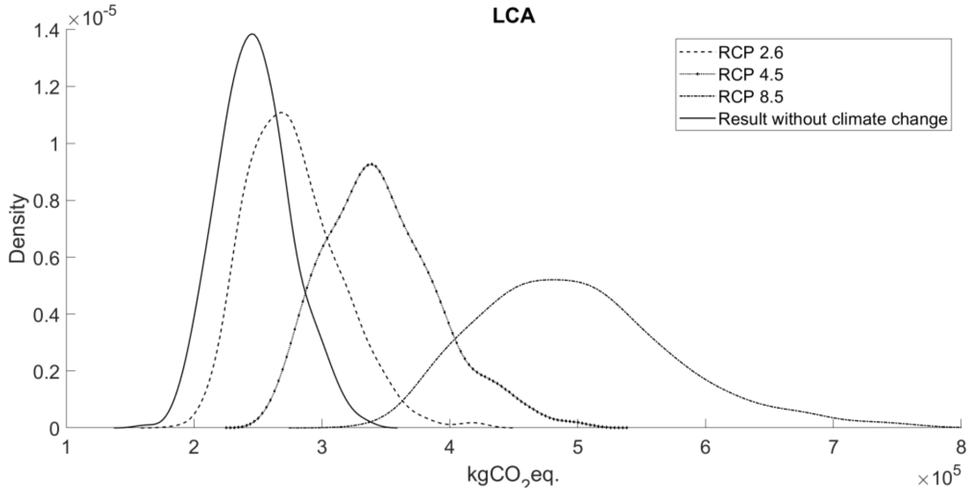

Figure 3. LCA distributions for the renovated building with RCP 2.6, 4.5 and 8.5. The straight line represents the response for a renovated building with climate data from SIA.

From Figure 4, it can be seen that even with the optimistic scenario of RCP 2.6, the renovation of the building stock is needed to lower the emissions over the building life cycle. Likewise with Figure 3, the results under current climate underestimate the total LCA (Figure 4).

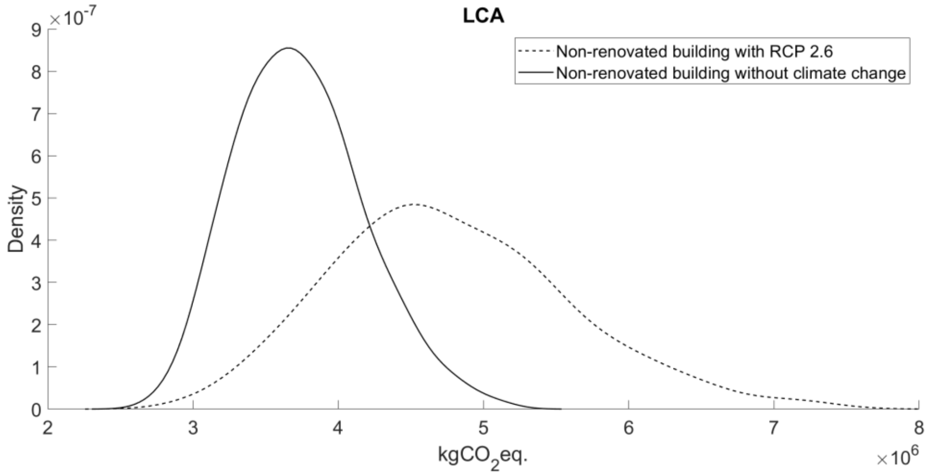

Figure 4. LCA distribution following a probabilistic assessment of the non-renovated building with RCP 2.6 and a response for the non-renovated building with climate data from SIA

For the LCC results, the picture is different. Even though the mean value for RCP2.6 (638 000 CHF) is lower than both RCP 4.5 (717 000 CHF) and RCP 8.5 (837 000 CHF), it can be seen that the standard deviation for RCP 2.6 (59 000 CHF) is relatively close to that of RCP4.5 (68 000 CHF).

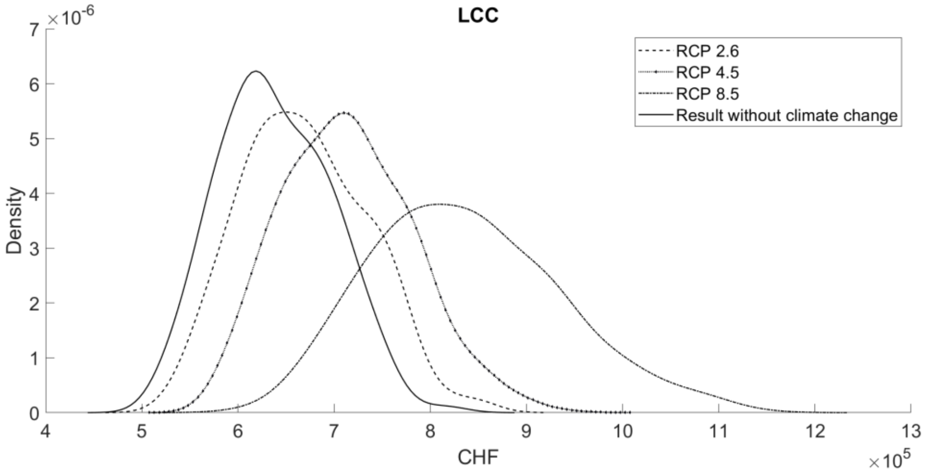

Figure 5. LCC results of the renovated building with RCP 2.6, 4.5 and 8.5 and probabilistic assessment with temperature data from SIA.

Similarly with the results of LCA, the results for LCC are shown in Figure 6.

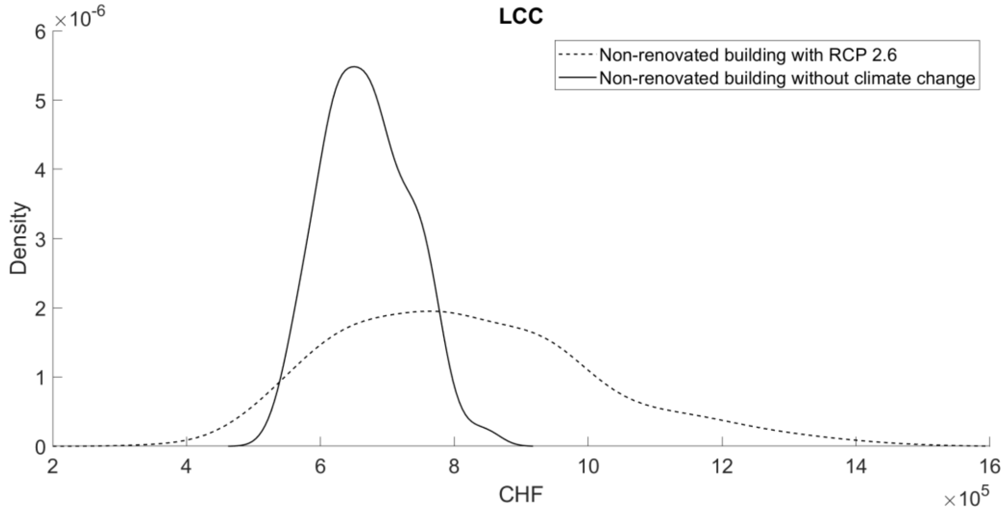

Figure 6. LCC distribution for the non-renovated building with RCP 2.6 and a response with calculations performed using data from SIA.

5. Discussion

The current results show the crucial role of thorough uncertainty quantification in both LCA and LCC analyses. It is clear that the analysis without climate change underestimates the values of LCA (3 736 000 CHF versus 4 775 000 CHF). For the LCC, the response of the analysis without climate change is relatively similar (686 800 CHF versus 817 000 CHF). Also, the results for all the climate change scenarios are considerably overlapping for LCC. This can be explained by the discount rate, which has to be adapted for all the LCC calculations and discount the future cash flows in order to convert them to a present value. Due to the long building life span of 60 years, discounted future cash flows are less influential and therefore, the climate change affects the costs less than the environmental impacts.

In this paper, we also compared a retrofitted building under three climate change scenarios with the non-renovated building under RCP2.6 as the most optimistic scenario. The results show that the renovated building under RCP8.5 has almost 10 times less emissions than the non-renovated building under the most optimistic scenario.

From the comparison with the calculations under current climate, it is clear that climate change has to be added in the analysis probabilistically as the results with the temperature values from the SIA standards leads to considerably underestimating the estimated of LCC and LCA values.

6. Conclusion

In this paper, a methodology for different climate change scenarios application in the integrated assessment of LCC and LCA was proposed. Daily temperature data from RCP 2.6, 4.5 and 8.5 were received from the National Center for Climate Services and processed into average monthly values to be included into LCC and LCA analyses. Three climate change scenarios were compared probabilistically for one renovation scenario of a residential multi-family apartment building located in Switzerland. Metamodeling techniques were used for uncertainty propagation and principal components analysis was applied in order to decrease the dimensionality of the problem. The results were compared with probabilistic calculations with the temperature data currently included in a Swiss standard [3]. The results show that the renovation scenario with RCP2.6 does not only have on average lower LCA than RCP 4.5 and RCP 8.5 but also comparing the standard deviation. The results also show that the climate change should be included in the renovation model probabilistically in order to use the LCC and LCA analyses in the decision making process.

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